Article

Estimation of carbon stock using ground inventory and remote sensing imagery in the case of Tiru-Selam Forest, North-western Ethiopia

E. Gezahegn Gashu, **M. Adamsew Marelign**
Department of Natural Resource Management, College of Agriculture and Environmental Science, University of Gondar, Gondar, Ethiopia
E-mail: gezahegngashu2009@gmail.com

Received 13 April 2022; *Accepted 20 May 2022*; *Published online 1 June 2022*; *Published 1 September 2022*

Abstract
Tiru-Selam forest is degraded due to human interventions. Several scholars have studied the carbon stock of various forests using combinations of ground inventory and remote sensing imagery without checking the correlation between these two carbon stock assessment methods. Thus, the study was conducted to determine the carbon stock of Tiru-Selam forest and the correlation of carbon stock estimated by ground inventory and remote sensing imagery. The ground inventory data was collected through a systematic random sampling technique from 400 m^2 of 72 sample plots, while the remote sensing imagery data was collected from the National Aeronautics and Space Administration (https://ladsweb.modaps.eosdis.nasa.gov). The moderate resolution imaging spectra-radiometer data was acquired with respect to the ground sampling date. Descriptive statistics were used to calculate the maximum, minimum, mean, and standard deviation of carbon stock. A linear regression model was used to estimate the correlation between ground inventory and remote sensing imagery for estimation of carbon stock in Tiru-Selam forest. According to the ground inventory, and the remote sensing imagery, the overall mean above-ground and below-ground carbon stock of the study area was estimated to be 224.6582 and 226.56 t/ha, respectively. The carbon stock estimated by ground inventory had a strong correlation with the normalized difference vegetation index (NDVI) ($r=0.742$, $p<0.05$) and the enhanced vegetation index (EVI) ($r=0.69$, $p<0.05$). The generated equations such as "Y" or estimated forest carbon stock = 302.2862 (EVI) + 239.8785(NDVI) + 24.11446 and Y = 301.9871 (EVI) + 237.2546 (NDVI) + 21.4254 have been fitted with vegetation indexes at $\alpha<0.05$.

Keywords ground inventory; remote sensing imagery; Tiru-Selam Forest; Ethiopia.

Computational Ecology and Software
ISSN 2220-721X
URL: http://www.iaees.org/publications/journals/ces/online-version.asp
RSS: http://www.iaees.org/publications/journals/ces/rss.xml
E-mail: ces@iaees.org
Editor-in-Chief: WenJun Zhang
Publisher: International Academy of Ecology and Environmental Sciences

1 Introduction
Tropical forests are an important source for carbon storage and climate change mitigation. It consists of the largest percentage of the world's forest biomass (FAO, 2011). Globally, it can hold around 80% of the total

above-ground carbon and 40% of the total below-ground carbon. About 15%–20% of global carbon emissions arise from deforestation and forest degradation in the tropics. It releases 60% of the carbon sequestered by forests (Gullison et al., 2007).

Deforestation and forest degradation can result in carbon emissions into the atmosphere, thus affecting the global climate and environment as a whole (Hansen et al., 2013). Deforestation accounts for 70% of the total greenhouse gas emissions in Africa (FAO, 2005). Ethiopian forest lands have been degraded due to rapid population growth, expansion of agricultural lands, and absence of sound management of forests (Moges et al., 2010), which led to a curve in the forest coverage of Ethiopia from 40 to 11.40% (FAO, 2015). Tiru-Selam Forest is one of the leftover dry Afromontane forests found in the northwestern parts of Ethiopia, and it is under the administration and management of the Amhara Regional government. Even though it is under management and pulling out of the forest is banned, the forest is still facing different troubles and problems, primarily from firewood collection, charcoal production, fencing, logging, firing, agricultural expansion, and cattle grazing by bordering communities of the forest. As a result, the most precious and imperative local or home-grown tree species are being exhausted and depleted in the area, with a corresponding emission of CO_2 into the atmosphere (Personal Observation, 2010-2020). Thus, the carbon stock assessment of Tiru-selam forest was conducted using a combination of ground inventory and remote sensing imagery, which provides logical quantitative data on carbon stock, climate change mitigation capacity, and correlation between ground inventory and remote sensing imagery for the study forest.

Nowadays, various approaches can be used for quantifying the carbon stock potential of forests in the global world. Among those approaches for estimation techniques of forest carbon stock, tree eco-models, a combination of ground measurements and biomass allometries and growth equations, and remote sensing-based approaches are the most common (Nowak and Crane, 2000). The most accurate method for estimating forest biomass is based on field measurements, but the collection of field measurements is time-consuming and labor-intensive, and it is impossible to census large geographic areas (Seidel et al., 2011). Geographic Information System (GIS)-based biomass estimation models cannot provide accurate biomass estimation because forest biomass often has weak relationships with environmental variables (Chen and Qi, 2013). But, the inter-combination of different approaches has good efficiency for quantifying carbon storage and carbon sequestration in forests (Rao et al., 2013).

Previous researchers have studied the carbon stock capacity of different forests using various approaches as follows. Vicharnakorn et al. (2014) assessed the carbon stock using remote sensing and forest inventory data in Savannakhet. Anurogo et al. (2018) saw a comparative approach to estimating forest aboveground carbon stock using advanced remote sensing technologies. Brilli et al. (2019) studied a combination of ground and remote sensing data to assess carbon stock changes in the main urban park of Florence. But none of the abovementioned researchers had studied the correlation of ground inventory and remote sensing imagery for carbon stock assessment on their study area. As a result, this study bridges the gap between the lack of quantitative data on the study forest's carbon stock and the gap of the aforementioned researchers.

2 Materials and Methods

2.1 Description of the study area

2.1.1 Location and area coverage

The study area is located in Hulet Eju Enese District, East Gojjam Zone of Amhara Region, North-western Ethiopia. It is located about 376 km to the northwest of the capital city of Ethiopia, Addis Ababa. Geographically, it is found between 37°44'30"E- 3750'10"E and 11°1'55'N-11°6’10"N (Fig. 1). The elevation range of the study area ranges from 1738m-2355m above sea level (masl) (Fig. 1). The area covered by the study forest is estimated to be 1330.25 hectare.

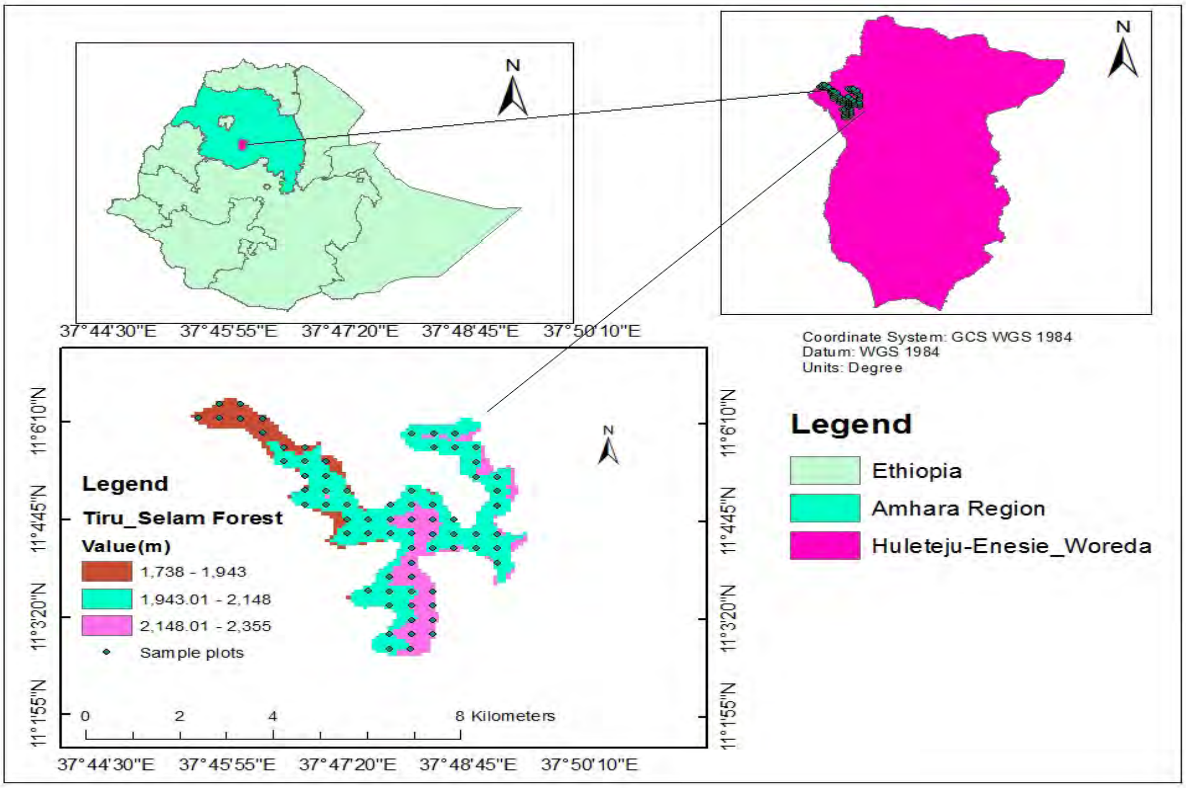

Fig. 1 Map of Tiru-Selam Forest.

2.1.2 Climate

Regarding the gridded figures obtained from the National Meteorological Weather Data (1988–2019), the mean maximum and minimum temperatures of the study area were 29.8°C and 13.78°C, respectively. The mean annual rainfall was also 1,686 mm (Fig. 2).

2.1.3 Vegetation types

Tiru-Selam Forest is composed of different natural tree species. It comprises many plant species, which are dominated mainly by *Carissa spinarum, Maytenus arbutifolia, Croton macrostachyus, Syzygium guineense, Allophylus abssinicus, Schefflera abyssinica, Rosa abyssinica, Dodonaea angustifolia, Albizia schimperiana, Ficus sur, Rhus retinorrhoea, Otostegia integrifolia,* and *Olea europaea subsp cuspidate* (Field survey, 2020).

2.2 Sampling technique

A systematic random sampling technique was employed to collect the ground inventory data, and the data was collected at every 200 meter interval between each sample plot and 300 meter intervals between each transect line. Finally, a total of 72 sample quadrants were plotted along the seven transect lines (Fig. 1).

2.3 Data collection for ground inventory

The entire trees and shrubs having ≥ 5 cm diameter at breast height (DBH) or diameter at shrub height (DSH) were sampled from 20 m × 20 m of sample plots using diameter tape following the methodology employed by Pearson et al. (2005). The height of those trees and shrubs was measured by an instrument called a hypsometer. Woody plants with several stems were considered and counted as a single tree at breast height, and the largest stem was taken. The botanical names and local names of all trees and shrubs were identified using Bekele's (1993) published Flora of Ethiopia and Eritrea.

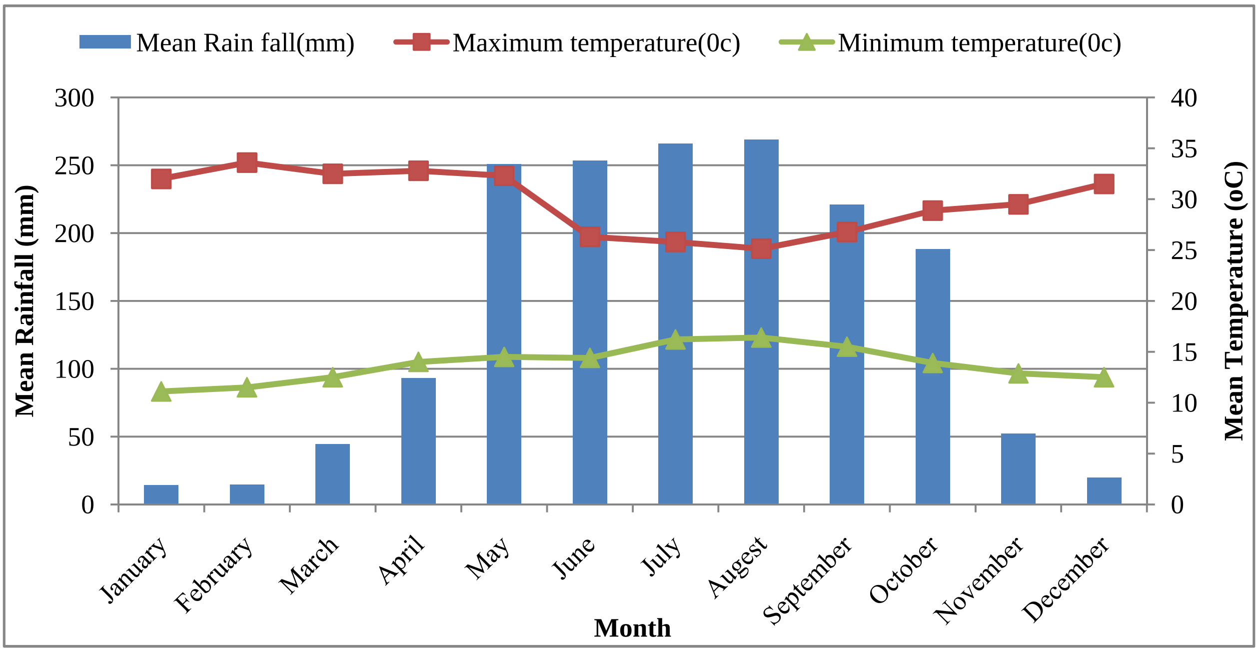

Fig. 2 Climate data of the study area (1988-2019).

2.4 Data collection for remote sensing imagery

The moderate resolution imaging spectra-radiometer (MODIS) vegetation indices were the products of 250 m × 250 m spatial resolution. The satellite data of "MYD13Q1.A2021025.h21v07.006.2021042002942" were obtained from the National Aeronautics and Space Administration (https://ladsweb.modaps.eosdis.nasa.gov) on January 16, 2020. Thus, this was similar to the dates of data collection at the field level. The MODIS satellite data acquisition had been considered the ground sampling date. The MYD13Q1 data is generated at 16-day intervals and at multiple spatial and temporal resolutions, providing consistent spectral vegetation indices.

Table 1 Descriptions of satellite datasets used in the study.

Satellite data	MODISMYD13Q1(NDVI, EVI)
Path/horizontal line number	20
Row/vertical line number	7
Spatial Resolution	250
Years	January 2020,and March 2020

2.5 Estimation of biomass and carbon stock capacity of Tiru-Selam Forest using ground inventory

2.5.1 Estimation of above-ground biomass and above-ground carbon stock

The above-ground biomass of trees and shrubs within Tiru-Selam forest was calculated using an allometric model developed by Chave et al. (2014) as shown below:

$$AGB = 0.0673 \times (\rho\, DBH^2 H)^{0.976} \quad (1)$$

where, *AGB* stands for aboveground tree biomass (kg), *DBH* stands for diameter of trees at breast height (cm), *H* stands for height of tree (m), *ρ* stands for wood density= (0.6 ton/m^3), which is the average value of wood density of trees in Africa (Henry et al., 2010). The above-ground carbon stock and above-ground biomass carbon dioxide equivalent of trees and shrubs within the study forest were calculated by following the methodology used by Pearson et al. (2005) and Pearson et al. (2007) as shown below.

$$\text{Above-ground carbon stock } (AGC) = \text{above ground biomass} \times 50\% \quad (2)$$

The above-ground biomass CO_2 equivalent

$$\mathrm{AGBCO_2\ eq} = AGC \times 3.67 \quad (3)$$

which is the molecular mass ratio of carbon dioxide to carbon.

2.5.2 Estimation of below- ground biomass and below- ground carbon stock

Below-ground biomass of trees and shrubs within the study forest was designed and determined by using root-shoot proportions of trees and shrub biomass, in which below-ground biomass of trees is 20% of the above-ground biomass of trees as suggested by MacDicken (1997). Below-ground carbon stock of trees and shrubs (BGC) within the study forest was estimated by multiplying below-ground biomass by 50%, following the methodology employed by Pearson et al. (2007). The quantity of below-ground biomass CO_2 equivalent (BGB CO_2 eq) found in the study forest was calculated by multiplying BGC with the molecular mass ratio of carbon dioxide to carbon (44/12) as recommended by Pearson et al. (2007).

2.5.3 Estimation of carbon stock in Tiru-Selam Forest using remote sensing imagery

The values of the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) were extracted from the MODIS data to estimate the carbon stock of the study forest using remote sensing imagery. The exact geographic coordinates of the sampling plots were obtained with the help of a geographical positioning system (GPS). Ground truth points were imported to generate vector data points in the Arc GIS environment, and the resulting vector data points were overlaid on the NDVI and EVI products to extract the NDVI and EVI values. The extracted NDVI and EVI values were regressed with the value of carbon stock estimated by ground inventory. To obtain the pixel values associated with the carbon stock of the forest, the NDVI equation was used as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (4)$$

where, *NDVI* = Normalized Difference Vegetation Index, *NIR* = Near Infrared Band, *Red* = Red Band. The EVI index equation was utilized to compare the indexes distribution values for the research area as it suggested by Huete et al. (1999) as the following:

$$EVI = 2.5 * \frac{(NIR - Red)}{(NIR + C1xRed - C2xBlue + L} \quad (5)$$

EVI = Enhanced Vegetation Index, *NIR* = Near Infrared Band, *Red* = Red Band, *Blue* = Blue Band, *C*1 = values as coefficients for atmospheric resistance Value 6, *C*2 = values as coefficients for atmospheric resistance value 7, *L* = the value to adjust for the canopy background. The correlations of ground inventory and *NDVI* & *EVI* values were calculated by the linear regression equation: y = a + bx.

The values of "a" and "b" have been calculated by using the following formula, employed by Pandey et al. (2019). y = Carbon value, x = NDVI value, b = coefficient and a = intercept and then, the correlation analysis is calculated using Pearson correlation test equation. Carbon stock map at pixel level was prepared using the best fit regression analysis using EVI and NDVI data. The forest carbon stock map was prepared by taking the average values of a, b and c coefficient values of equations and the smaller root mean square error (RMSE) of the best fitted regression analysis in the study site. The estimated carbon stock was validated using the carbon stock estimated by ground inventory to assess the accuracy of the model (approach). Regression coefficients and goodness of fit statistics (R^2 and RMSE) have been prepared to check the accuracy of the model.

2.6 Statistical analysis

Descriptive statistics were used to calculate the maximum, minimum, mean, and standard deviation of carbon stock estimated by the method of ground inventory. Linear regression was used to estimate the correlation of carbon stock estimated by ground inventory and remote sensing imagery.

3 Results and Discussion

3.1 Carbon stock of Tiru-Selam Forest using the ground inventory method

According to the data obtained through ground inventory, the overall mean minimum and mean maximum above ground and below ground carbon stock of the study forest was estimated to be 9.41 (sample plot 40) and 351.41 t/ha (sample plot 28) respectively (Fig. 3). The variation of carbon stock among 72 sample plots could be due to the variation in height & DBH of trees and height & DSH of shrubs in the study forest. The overall mean above ground and below ground carbon stock of the study area was estimated to be 224.6582±63.00985 t/ha, which sequestered 824.4956±231.2461 t/ha CO_2 equivalent (Fig. 3). The overall mean above ground and below ground carbon stock of Tiru-Selam forest estimated by ground inventory (224.6582 t/ha) was lower than the overall mean above ground and below ground carbon stock of Banja forest (450.46 t/ha) (Abere et al. 2017), Sekele-Mariam forest (435.27 t/ha) (Ewunetie et al., 2021) and Dirmaga Watershed (316.27 t/ha)(Marelign and Melese, 2022). It also greater than the overall mean above-ground and below-ground carbon stock of Humbo forest (158.65 t/ha)(Chinasho et al., 2015) and Behertsige central closed park in Addis Ababa (30.5 t/ha)(Tefera and Soromessa, 2015). The carbon stock variation among the aforesaid areas could be due to the difference in climatic conditions and the corresponding height & DBH class of trees.

3.2 Values of NDVI and EVI for sample plots in the study area

The minimum and maximum NDVI values of sample plots in the study area were estimated to be 0.040182 (sample plot 67) and 0.719587 (sample plot 63), respectively (Fig. 4). The minimum and maximum EVI values of sample plots in the study area were estimated to be 0.022069 (sample plot 67) and 0.487408 (sample plot 64), respectively (Fig. 4). The mean NDVI value in the sample plot of the study forest was also estimated to be 0.47261±0.160268.

The variation of EVI and NDVI within the sample plot of the study area could be due to the difference in land use land cover and vegetation status of sample plots.

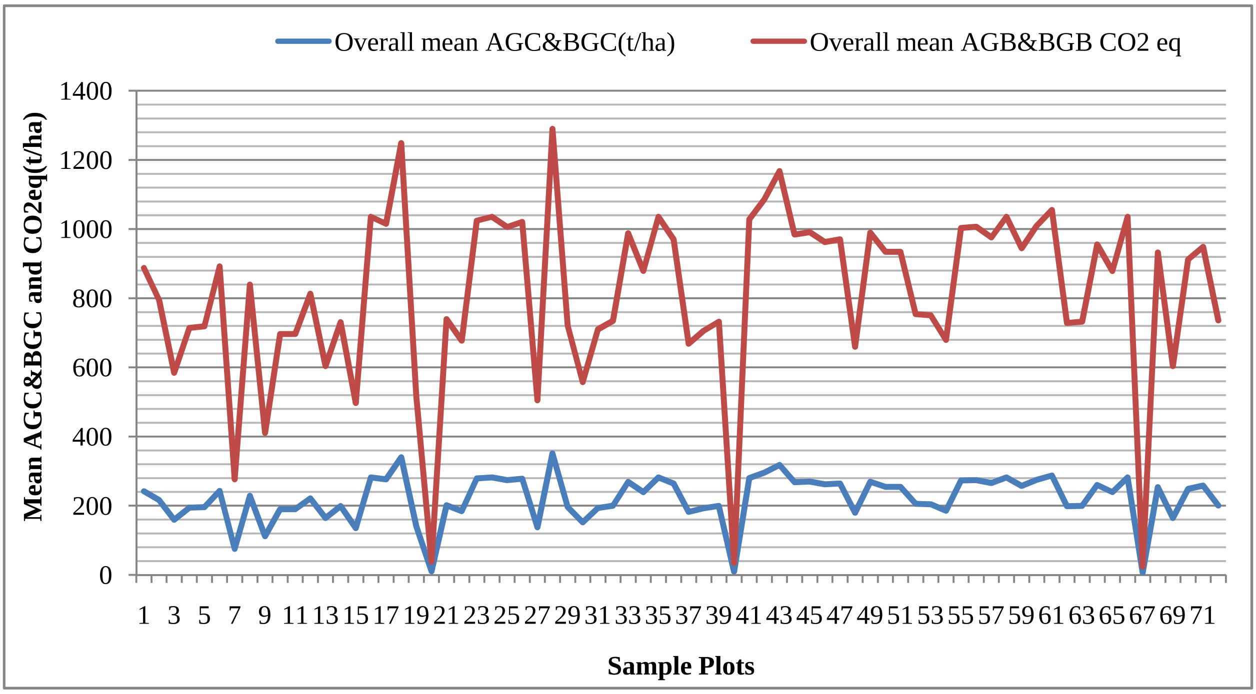

Fig. 3 Over all mean AGC and BGC & CO2 equivalent in the sample plot of the study area.

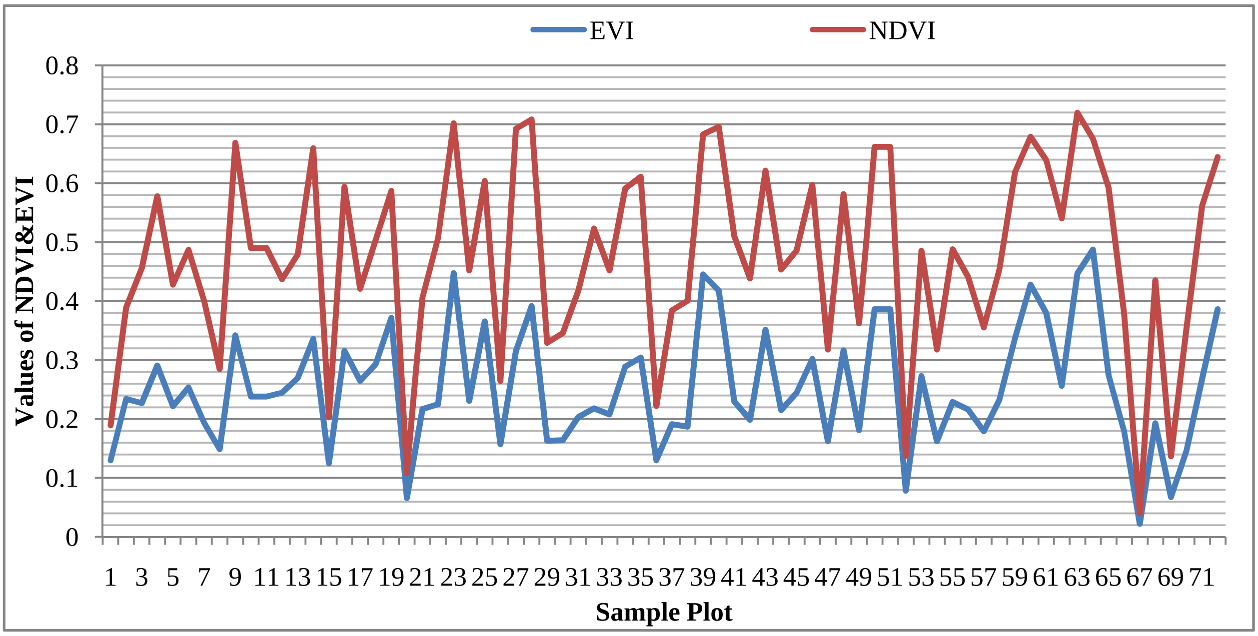

Fig. 4 NDVI and EVI values of sample plots in the study area.

3.3 Carbon stock of Tiru-Selam Forest using remote sensing imagery

3.3.1 The spatial distribution of NDVI and EVI in the study forest

According to the remote sensing data, the minimum and the maximum normalized deference vegetation index of the study area were estimated to be -15.8582 and 0.822843, respectively (Fig. 5). The negative value of NDVI in the study forest refers to forest areas with water surfaces, manmade structures, rocks, and clouds, while the maximum vegetation index, particularly above 0.6, indicates the dense vegetation part of the study forest. The moderate value of NDVI (0.2-0.3) also refers to forest areas with shrubs and grassland. Moreover, the values of NDVI indicate the amount of chlorophyll content present in vegetation, where a higher NDVI value indicates dense and healthy vegetation, and a lower value indicates sparse vegetation or bare soil. Thus, regions assigned higher NDVI values are because of relatively higher reflectance values in the NIR and lower in the red band to monitor vegetation health, changes, types, amounts, and conditions (Pandey et al., 2019). The NDVI indicates the photosynthetically active radiation for vegetation that is strongly affected by climatic conditions and surrounding factors such as soil and geomorphology, as well as physico-chemical characteristics of the plant and leaf texture (Rani et al., 2018). It combines the near-infrared reflectance and red channels into a single band image with values ranging from 1 to +1.

According to the spatial distribution of the enhanced vegetation index, the minimum and maximum enhanced vegetation index was estimated to be -0.0243974 and 0.647374, respectively (Fig. 5). The EVI of a forest is similar to the NDVI, which can be used to assess vegetation greenness. Accordingly, the maximum and moderate values of EVI indicate dense vegetation and shrub land or grass land, respectively. The negative value of EVI indicates the water bodies and rock surfaces of the study forest.

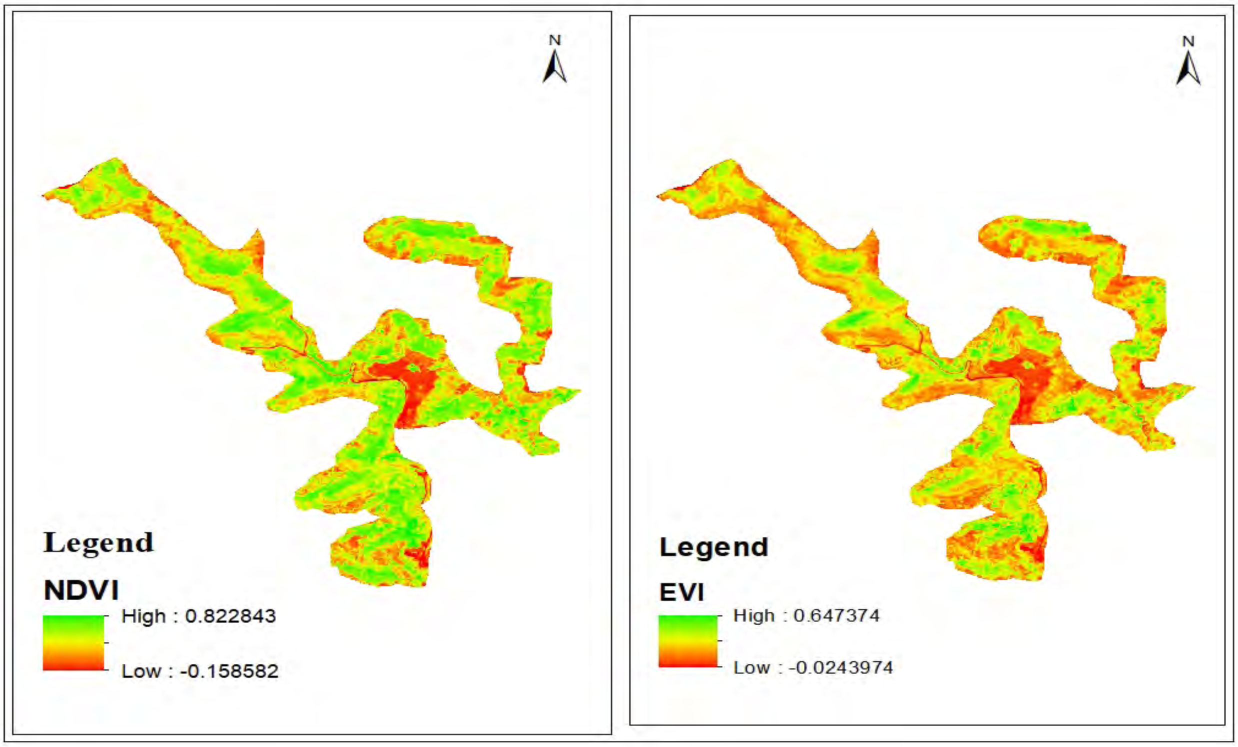

Fig. 5 Spatial distribution of NDVI and EVI.

3.3.2 Spatial distribution of carbon stocks using remote sensing imagery

According to the collected remote sensing data since January 2020 and March 2020, the minimum and maximum carbon stock potential of Tiru-Selam forest were estimated to be zero and 411.856 t/ha, respectively. According to the satellite data, the mean carbon stock of the study forest was estimated to be 226.56 t/ha. The zero t/ha carbon stock refers to the part of the study area that had no annual grass and vegetation cover. The vegetation cover of the study forest was different in the two seasons (January and March) (Fig. 6).

The temporal and spatial variation in the distribution of carbon stock in the study area could be due to the effect of rainfall. According to the field observation of the authors from 2018–2020, the study area had gotten rainfall starting from the beginning of March, and the annual grasses are being grown. According to the overall spatial distribution map of the study area (Fig. 7), the largest area coverage of the study forest (684.21 ha) had relatively medium carbon stock, which ranges from 150.01-300 t/ha, with an area coverage of 51.43% (Table 1). On the contrary the least area coverage of the study forest was occupied by relatively high carbon stock (300.01-411 t/ha), which covered 5.32% of the study area (Table 2).

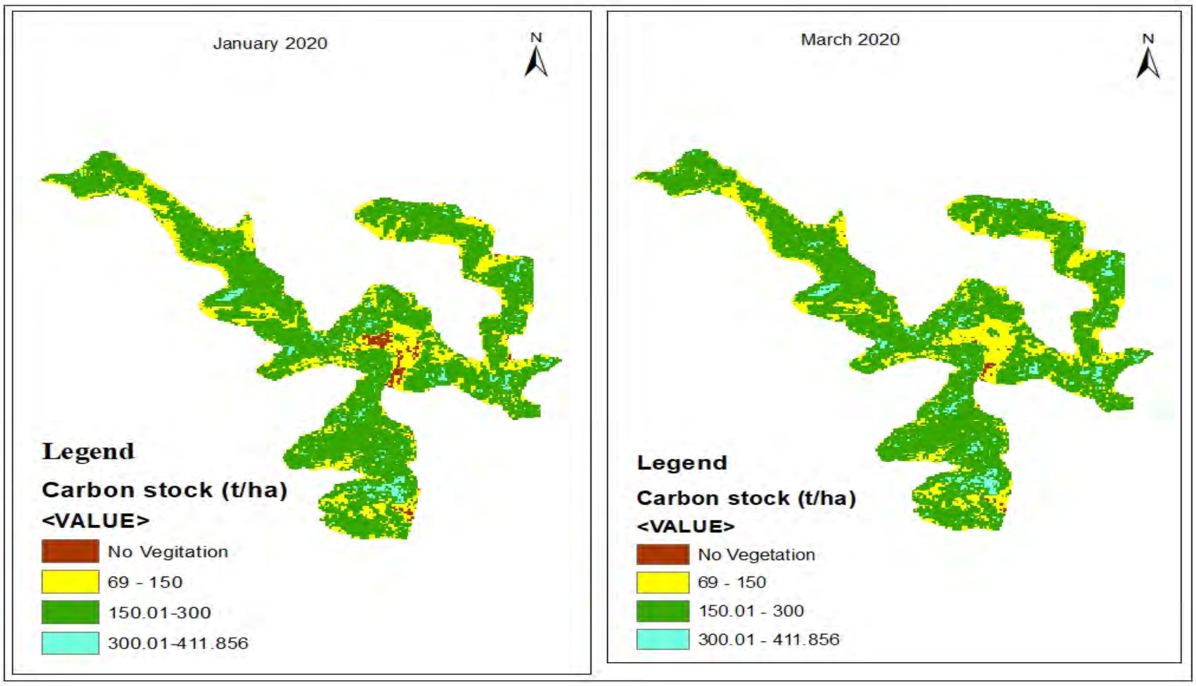

Fig. 6 Spatial distribution of carbon stock (t/ha).

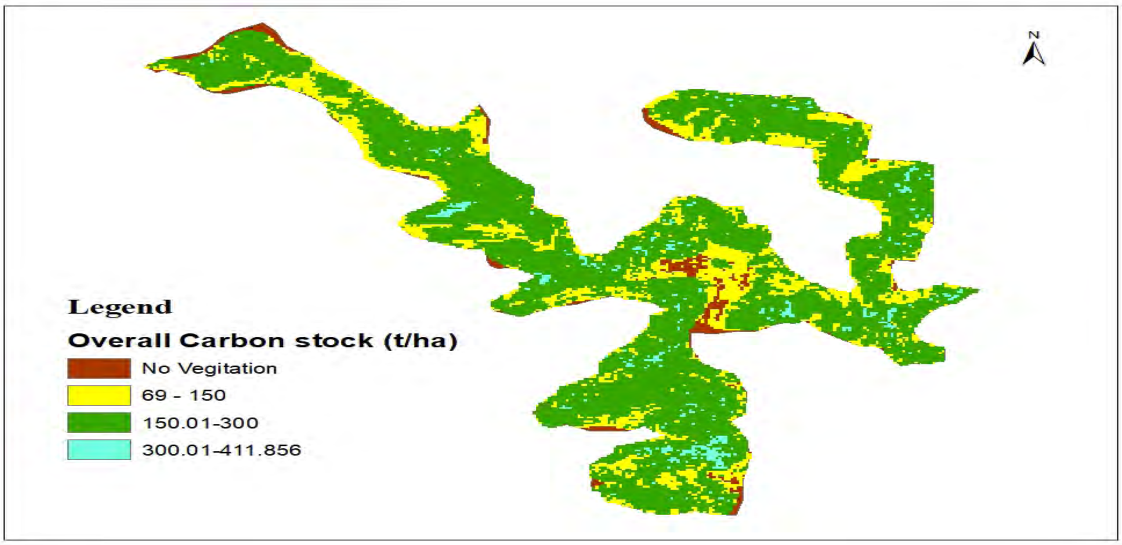

Fig. 7 Over all spatial distribution of carbon stock (t/ha).

Table 2 Area coverage (ha & %) of carbon stock classes in the study forest.

Carbon Stock Class	Area(ha)	Area (%)
No Vegetation	341.2	25.65
69-150(t/ha)	234.09	17.6
150.01-3009(t/ha)	684.21	51.43
300.01-411(t/ha)	70.75	5.32
Mean carbon stock =226.56t/ha	Total area=1330.25	Total area=100

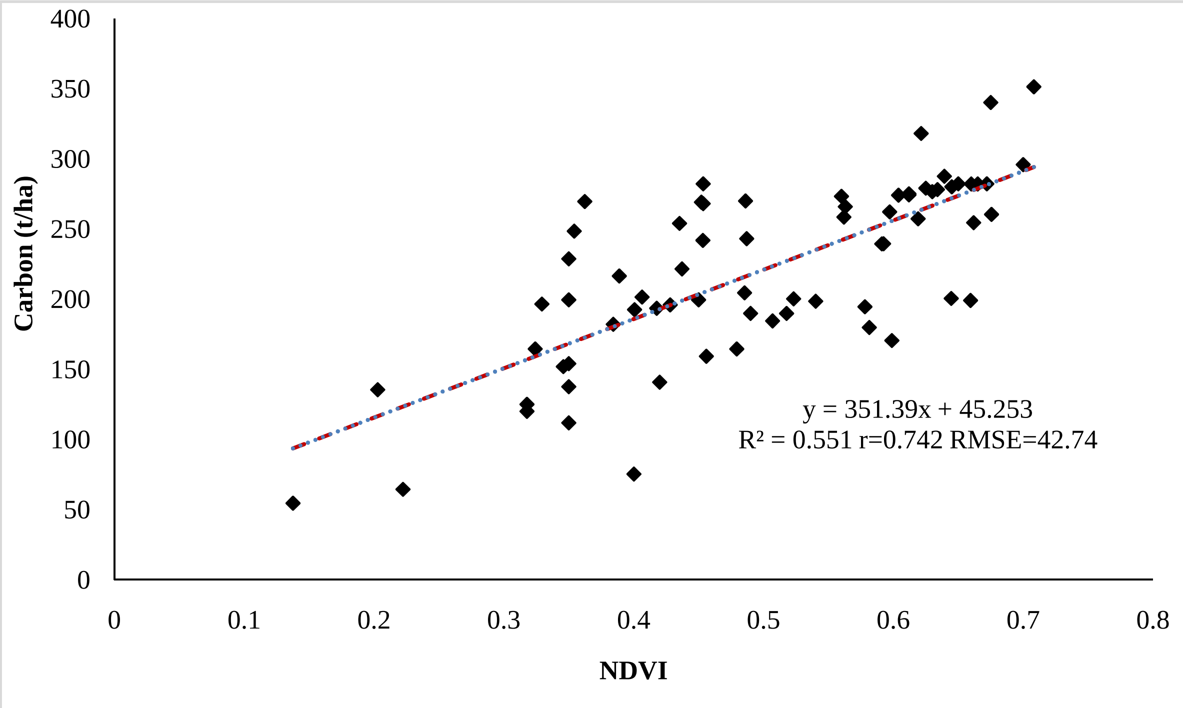

Fig. 8 Linear regression between carbon stock estimated by ground inventory and NDVI.

3.4 Development of regression models

The mean carbon stock of the Tiru-Selam forest estimated by ground inventory was estimated to be 224.6582±63.00985 t/ha and the NDVI value of the study forest ranged from -15.8582 to 0.822843 (Fig. 5). The EVI of the study area also ranged from-0.0243974 to 0.647374 (Fig. 5). The amount of carbon stock estimated by ground inventory had a strong correlation with the NDVI of the study area ($r = 0.742$; $p<0.05$) (Fig. 8). The carbon stock estimated by ground inventory had a strong correlation with the EVI of the study area ($r = 0.69$; $p<0.05$) (Fig. 9). The linear regression model between carbon stock estimated by ground inventory and NDVI had generated an equation: $y = 135.39x + 45.253$ at $p<0.05$, where y = estimated forest carbon stock, 135.39 and 45.253 are regression coefficients, and x is the NDVI value (Fig. 8). Similarly, another regression model between the carbon stock estimated by ground inventory and EVI has generated an equation: y = 595.69x + 69.144, at $p<0.05$, where y = predicted forest carbon stock, 595.69 and 69.144 are regression coefficients, and x is the EVI value (Fig. 9).

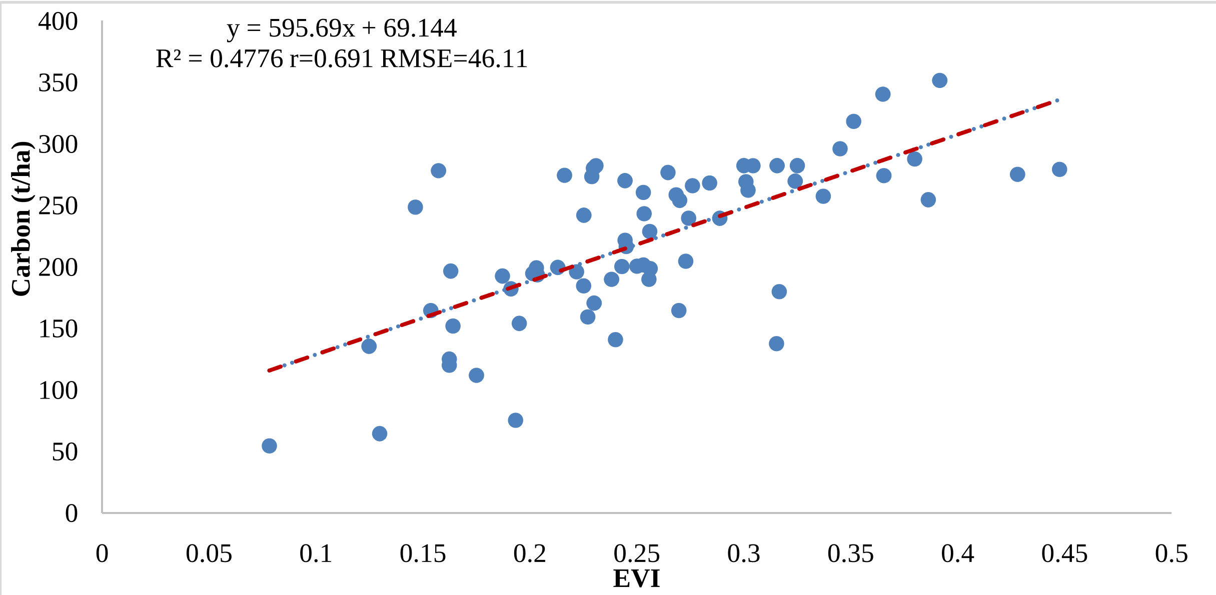

Fig. 9 Linear regression between carbon stock estimated by ground inventory and EVI.

3.5 Goodness of fit statistics for the model developed from vegetation indices

The study considered the effectiveness of MODIS vegetation indices for estimating carbon stock using a best-fit regression model. The spatial distribution of NDVI shows a large area is covered by vegetation (Fig. 5), which reflects the distribution of healthy and dense vegetation in the study area. Most of the areas had higher EVI and NDVI values (Fig. 5), which indicates that EVI and NDVI are correlated. The value of R^2 was estimated to be 0.6185 (p=0.0001) for equation Y = 302.2862(EVI) + 239.8785(NDVI) + 24.11446 and the data fit the regression model (Table 3). The value of R^2 was estimated to be 0.605 (p=0.0001) for equation Y = 301.9871(EVI) + 237.2546(NDVI) + 21.4254) (Table 3). This revealed that the model is predictive under the conditions of its intended use.

Table 3 Generated equations and goodness of fit statistics for the model developed from vegetation indices.

	Equation	RMSE	R^2	p
Model Calibration	Y=302.2862 (EVI)+239.8785 (NDVI)+24.11446	0.39	0.6185	0.0001
Model Validation	Y=301.9871 (EVI)+237.2546 (NDVI)+21.4254	0.42	0.605	0.0001

4 Conclusion

Ground inventory and satellite imagery are widely used for the reliable estimation of forest carbon stock. According to the ground inventory and remote sensing imagery, the overall mean above-ground and below-ground carbon stock of the study area was estimated to be 224.6582 and 226.56t/ha, respectively. The carbon stock estimated by ground inventory was strongly correlated with NDVI ($r = 0.742$, $p<0.05$) and EVI ($r = 0.69$, $p<0.05$). The developed equations, such as $Y = 302.2862(EVI) + 239.8785(NDVI) + 24.11446$ and $Y = 301.9871(EVI) + 237.2546(NDVI) + 21.4254$, had good fitness with the MODIS data at $\alpha=0.05$.

Acknowledgment

The authors are thankful to data collectors such as Tenaw Munye and Gashaw Alemante

References

Abere F, Belete Y, Kefyalew A, Soromessa T. 2017. Carbon stock of Banja forest in Banja district, Amhara region, Ethiopia: an implication for climate change mitigation. Journal of Sustainable Forestry, 36: 604-622

Anurogo W, Sari LR, Lubis MZ, Pamungkas DS, Mufida MAK, Situmorang ADL. 2018. An integrated comparative approach to estimating forest aboveground carbon stock using advanced remote sensing technologies. International Conference on Applied Engineering (ICAE). 1-6, IEEE

Bekele A. 1993. Useful trees and shrubs for Ethiopia: identification, propagation and management for agricultural and pastoral communities. RSCU/SIDA

Brilli L, Chiesi M, Brogi C, Magno R, Arcidiaco L, Bottai L, Maselli F. 2019. Combination of ground and remote sensing data to assess carbon stock changes in the main urban park of Florence. Urban Forestry and Urban Greening, 43: 126377

Chave J, Réjou-Méchain M, Búrquez A, Chidumayo E, Colgan MS, Delitti WB, Vieilledent G. 2014. Improved allometric models to estimate the aboveground biomass of tropical trees. Global Change Biology, 20(10): 3177-3190

Chen Q, Qi C. 2013. Lidar remote sensing of vegetation biomass. Remote Sensing of Natural Resources, 399: 399-420

Chinasho A, Soromessa T, Bayable E. 2015. Carbon stock in Woody plants of Humbo forest and its variation along altitudinal gradients: the case of Humbo district, Wolaita Zone, Southern Ethiopia. Journal of Environmental Protection and Policy, 3: 97-103

Ewunetie GG, Miheretu, BA, Mareke GT. 2021. Carbon stock potential of Sekele Mariam forest in North Western Ethiopia: an implication for climate change mitigation. Modeling Earth Systems and Environment, 7: 351-362

FAO (Food and Agricultural Organization of the United Nations). 2005. The State of World'S forests. Global Forest Resource Assessment. Main report, FAO forest paper 163, Rome, Italy

FAO (Food and Agricultural Organization of the United Nations). 2015. Global Forest Resources Assessment. Desk Reference. Rome, Italy

FAO (Food and Agriculture Organization of the United Nations). 2011. State of World's Forest. FAO: Rome, Italy

Gullison E, Frumhoff PC, Canadell JG, Field CB, Nepstad DC, Hayhoe K, Nobre C. 2007. Tropical forests and climate policy. Science, 316(5827): 985-986

Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Townshend J. 2013.

High-resolution global maps of 21st-century forest cover change. Science, 342(6160): 850-853

Henry M, Besnard A, Asante WA, Eshun J, Adu-Bredu S, Valentini R, Saint André L. 2010. Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. Journal of Forest Ecology and Management, 260(8): 1375-1388

Huete A, Justice C, van Leeuwen W. 1999. MODIS vegetation index (MOD13). Algorithm Theoretical Basis Document, 3(213): 295-309

MacDicken KG. 1997. A Guide To Monitoring Carbon Storage In Forestry and Agro Forestry Projects In Forest Carbon Monitoring Program. Winrock International Institute for Agricultural Development, Arlington, Virginia, USA

Marelign MA., Mekonen DT. 2022. Estimating and mapping woodland biomass and carbon using Landsat 8 vegetation index: A case study in Dirmaga Watershed, Ethiopia. Computational Ecology and Software, 12(2): 67-79

Moges Y, Eshetu Z, Nune S. 2010. Manual For Assessment and Monitoring of Carbon In Forest and Other Land Uses In Ethiopia (Draft). Ethiopian Forest Research Center, Addis Ababa, Ethiopia

Nowak DJ, Crane DE. 2000. The Urban Forest Effects (UFORE) Model: quantifying urban forest structure and functions. In: Integrated tools for natural resources inventories in the 21st century (Hansen M, Burk T, eds). 714-720, US Dept. of Agriculture, Forest Service, North Central Forest Experiment Station, MN, USA

Pandey PC, Srivastava PK, Chetri T, Choudhary BK, Kumar P. 2019. Forest biomass estimation using remote sensing and field inventory: a case study of Tripura, India. Environmental Monitoring and Assessment, 191(9): 1-15

Pandey PC, Anand A, Srivastava PK. 2019. Spatial distribution of mangrove forest species and biomass assessment using field inventory and earth observation hyperspectral data. Biodiversity and Conservation, 28(8): 2143-2162

Pearson T, Walker S, Brown S. 2005. Sourcebook for Land Use, Land Use Change and Forestry Projects. Winrock International and the Bio Carbon Fund of the World Bank, Arlington, USA

Pearson, TR, Brown SL, Birdsey RA. 2007. Measurement Guidelines For The Sequestration of Forest Carbon. 6-15, Northern Research Station, Department of Agriculture, Washington DC, USA

Rani M, Dhok SB, Deshmukh RB. 2018. A systematic review of compressive sensing: Concepts, implementations and applications. IEEE Access, 6: 4875-4894

Rao P, Hutyra LR, Raciti SM, Finzi AC. 2013. Field and remotely sensed measures of soil and vegetation carbon and nitrogen across an urbanization gradient in the Boston metropolitan area. Urban Ecosystems, 16(3): 593-616

Seidel D, Fleck S, Leuschner C, Hammett T. 2011. Review of ground-based methods to measure the distribution of biomass in forest canopies. Annals of Forest Science, 68(2): 225-244

Tefera M, Soromessa T. 2015. Carbon stock potentials of woody plant species in Biheretsige and Central Closed Public Parks of Addis Ababa and its contribution to climate change mitigation. Environmental Earth Sciences, 5(13): 1-14

Vicharnakorn P, Shrestha RP, Nagai M, Salam AP, Kiratiprayoon S. 2014. Carbon stock assessment using remote sensing and forest inventory data in Savannakhet, Lao PDR. Remote Sensing, 6(6): 5452-5479